System versus Human: The Role of Trusting Beliefs in AI Adoption Across Personal and Work Contexts

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ABSTRACT

As Large Language Models (LLMs), such as ChatGPT and Microsoft Copilot, become increasingly integrated into daily life, understanding how users form trust in these AI systems can aid in promoting adoption and sustained use of the technology. While previous research has examined trust in technology from a functional perspective, LLMs challenge this view by showing system-like capabilities with human-like interaction features. This raises the question of how different types of trust, system-like and human-like, form user evaluations for a LLM.

This thesis investigates how human-like trusting beliefs (such as integrity, competence, and familiarity) and system-like trusting beliefs (including reliability, functionality, helpfulness, and privacy/security) influence four key user outcomes: perceived usefulness, perceived enjoyment, trusting intention, and continuance intention. It also examines whether the context in which a large language model (LLM) is used, personal versus work-related, moderates these relationships. The study uses a dual trust framework and is supported by theories that emphasize how trust in technology is formed by both system characteristics and the environment in which technology is used.

A survey design was employed with a sample of 150 participants, who were randomly assigned to reflect on either personal or professional use of an LLM. Participants reported their experiences with the LLM in the context they most often used it and completed validated measures of trusting beliefs and user outcomes.

The results show that system-like trust was the most consistent and significant predictor across all outcomes. Human-like trust showed a more selective influence, contributing significantly to continuance intention. Importantly, context played a significant moderating role, particularly strengthening the effect of trust on continuance intention.

This study contributes to theory by validating the dual-trust framework in the context of LLMs and by showing that trust formation can be context-sensitive. Practically, the findings suggest that LLM designers and organizations should tailor their systems and messaging to match user expectations across different settings but specifically focus on system-like trust. Future research should explore how trust evolves over time, and how other factors, such as culture and experience, form trust in AI assistants.

KEYWORDS: trust in AI, large language models, human-like trust, system-like trust, usage context, AI adoption, ChatGPT

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Table of Contents

Chapter 1: Introduction

Artificial Intelligence (AI) assistants, particularly Large Language Models (LLMs) such as ChatGPT and Co-Pilot, are increasingly being adopted across a wide range of fields. These models are trained on large collections of data to generate human-like language and have conversations, making them helpful for solving problems, giving advice, creating content, and answering questions (Chen & Park, 2021, p. 2722). They are used in many different settings, from personal productivity and education to healthcare, customer service, and marketing (Afroogh et al., 2024, p. 6). LLMs are no longer just seen as tools for automating simple tasks; they are now often viewed as systems that can support more complex interactions and even take part in decision-making (Bao et al., 2021, p. 607). This growing presence of LLMs shows how much they are starting to influence daily life. They are increasingly being integrated into various contexts and tools, such as online shopping chatbots, in-car voice assistants, hospital robots, and educational apps (Afroogh et al., 2024, p. 10; Hu et al., 2021, p. 1).

Despite the growing use of LLMs, critical questions are being raised about trust in AI. Users often struggle to understand how these AI models generate responses due to their complexity and lack of transparency, which can lead to concerns about reliability and privacy (Chen & Park, 2021, p. 2723; Yu et al., 2023, p. 460). This an important issue as a lack of trust in AI can result in resistance to technology adoption, with users feeling uncertain or even threatened by its capabilities (Svenningsson & Faraon, 2019, p. 153). Understanding how trust in AI is formed and maintained is important to increase widespread acceptance (Afroogh et al., 2024, p. 2).

Research shows that trust in technology is formed by how users perceive it, specifically, whether it feels more human-like or machine-like. People often anthropomorphize technology, attributing human traits to systems that display social cues (Chen & Park, 2021, p. 2723). LLMs occupy a unique position between functional tools and social actors. On the one hand, they can help users complete tasks efficiently and accurately, such as traditional software. On the other hand, their conversational style, natural language fluency, and often empathetic tone allow users to interact with them in more human-like ways (Chen & Park, 2021, p. 2722). This perception plays a role in which trusting beliefs, such as integrity, competence, or reliability, eventually become most important for trusting the technology and continuing to use it (Lankton et al., 2015, pp. 880-918).

Lankton et al. (2015) offer a useful framework that explains how trusting different beliefs vary depending on whether a system is seen more as a human or more like a tool, based on several underlying dimensions. They specifically distinguish between human-like and system-like trust. Although Lankton et al. (2015) investigated how trust dimensions vary between a high-humanlike technology in a personal context and a low-humanlike system in a classroom setting, entirely different technologies. This study focuses on AI-assistants which can display both human and system-like features.

In forming trust in LLMs, the role of context as a moderating influence has not yet been examined in depth. This is important to note, as prior research has consistently acknowledged the influence of contextual factors in forming trust, such as organizational norms, social dynamics, and task characteristics (Hsieh & Lee, 2024, pp. 620–622; Sung et al., 2023, p. 1772). Scholars have suggested that different trust dimensions may become more relevant depending on the context. For example, competence may matter more in professional settings, while warmth or integrity may be more important in personal interactions, depending on users' goals and expectations (Lankton et al., 2015, p. 884; Chen & Park, 2022, pp. 2732–2733). These insights are, however, based largely on systems that are either clearly functional or clearly social. For technologies such as LLMs, which blend system-like features with human-like interaction, it remains unclear which type of trust plays a more central role in different contexts, or how these roles may shift between personal and professional use.

To gain a more complete understanding of how context moderates the influence of different trust types, this study draws on Social Cognitive Theory (Califf et al., 2020), Affordance Theory (Gibson, 1977), and Lankton et al.'s (2015) dual trust framework. Specifically, it examines how personal versus professional settings influence the relationship between perceived humanness and trust in LLMs, and the presence of human-like versus system-like trust in these contexts. The formation of trust includes four outcome variables: perceived usefulness, perceived enjoyment, trusting intention, and continuance intention. These outcomes were selected based on their relevance to long-term technology use and their presence in the trust and adoption literature (Lankton et al., 2015, pp. 880–918).
The central question of this thesis will be:

"How do human-like and system-like trusting beliefs influence user outcomes (perceived usefulness, perceived enjoyment, trusting intention, and continuance intention) in the use of Large Language Models, and how is this relationship moderated by the context of use (personal vs. work-related)?"

This question builds on previous research on trust in technology, where recent work by Lankton et al. (2015) distinguishes between two types of trusting beliefs: system-like (e.g., reliability, functionality, privacy) and human-like (e.g., integrity, competence, familiarity). While this dual framework has been explored in relation to digital agents and technologies, it has not yet been widely applied to LLMs, nor has the influence of context been examined in detail.

The study contributes to the academic field of trust in technology in two main ways. First, it adds to the growing literature on trust in AI by adopting a multidimensional view of trust, distinguishing between human-like and system-like beliefs (Lankton et al., 2015, p. 893). While trust in technology is often measured as a single construct, Lankton et al. (2015) argue that users may apply different types of trust, human-like or system-like, depending on how socially present or human-like the technology appears. This study contributes to that line of thinking by examining how these different types of trusting beliefs may lead to different outcomes in interaction with AI systems.

Second, it introduces context as a moderating factor, addressing a gap in current trust literature. Although scholars have acknowledged that trust can be influenced by contextual factors (Lankton et al., 2015, p. 884), it remains unclear how the same AI system may be trusted differently depending on the setting in which it is used. By comparing personal and professional contexts, this study examines how trust in LLMs develops based on the environment and context of use.

From a practical perspective, the findings can help AI developers and organizations better align their systems with user expectations. Prior work has shown that trust influences both acceptance and continued use of intelligent systems (Afroogh et al., 2024, p. 1; Shoabjareh et al., 2024, p.2). Trust is seen as a key factor in improving the design, development, and deployment of AI systems, as it helps align technology with user expectations (Afroogh et al., 2024, p. 12). For AI developers, this study can offer guidance on how to design systems that match what users need and value in different settings. It also provides insights into which trusting dimensions, such as reliability or warmth, are considered most important in different contexts. For example, in professional environments, emphasizing reliability and performance may foster trust (Yu et al., 2023, p. 456)., while in personal contexts, warmth and familiarity may be more important (Hsieh & Lee, 2024, p. 619). Organizations that understand these trust formations can create more effective strategies to foster trust in AI and fully maximize the business potential of LLMs (Hu et al., 2021, p. 1).

This thesis explores how the nature of a system and the context in which it is used interact to form trust. It integrates human-like and system-like beliefs into a single model, links them to key user outcomes, and investigates how these relationships change between personal and professional domains.

Chapter 2: Theoretical Framework

This chapter outlines the theoretical foundation for examining how users form trust in AI systems, particularly Large Language Models (LLMs). It begins by introducing the general concept of trust and distinguishing between trust in humans and in technology. It then discusses the framework developed by Lankton et al. (2015), which differentiates between human-like and system-like trust dimensions. Their work demonstrates how users can form different types of trust depending on how human-like or machine-like a system appears.

Moreover, this chapter explores how context of use, whether the LLM is used in a work-related or personal setting, can affect which trust dimensions are more influential. Context influences not only user expectations, but also which features of the technology are focused on during interaction. This framework allows for a more flexible and nuanced understanding of trust in AI systems that blend functional and relational features.

2.1 Trust in Humans and Trust in Technology

Trust plays a key role in whether people adopt and continue using new technologies. Trust in technology has therefore been widely studied. After all, individuals, organizations, and societies can only really benefit from a new system when it meets their expectations, not just during development, but also when it's implemented and used on a daily basis (Afroogh et al., 2024, p. 2).When users do not trust a system, they may feel uncertain or even threatened by its capabilities (Afroogh et al., 2024, p. 1). This is especially true for AI systems, which often are perceived as complex or unpredictable. Their so-called "black box" nature, where it is unclear how inputs are transformed into outputs, makes them difficult for users to understand, and in turn, harder to trust (Afroogh et al., 2024, pp. 9-20).

Traditionally, technology has been viewed as a set of tools: functional, efficient, and predictable. In this view, users are expected to make rational decisions about whether to trust a system based on things such as reliability and ease of use (Lankton et al., 2015, p. 883). Trust in people is more relational and based on qualities such as shared values, ethical behavior, or the ability to understand others. Human trust often stems from the expectation that others will act with integrity and empathy (Lankton et al., 2015, p. 883).

In practice, the line between trust in humans and in technology is not always clear. Even though technology is not human, people often perceive it in human-like terms. Lankton et al. (2015, p. 884) propose that even technologies can be perceived as possessing human-like characteristics. People tend to anthropomorphize technology, positioning it along a "humanness continuum." At one end, technology is perceived as purely functional and valued for its efficiency and reliability. At the other end, it is seen as socially responsive, emotionally intelligent, and capable of understanding user needs. Where a technology falls on this humanness continuum is not fixed but depends on individual perceptions, making the human-like interpretation inherently subjective.

The study by Lankton et al., (2015) presents a framework that distinguishes trust in technology from human-like and system-like trust. They argue that how human-like a technology feels affects which type of trust users rely on. For example, if a system includes a voice or interactive features, people are more likely to apply human-like trust. If the system feels more technical or task-focused, users trust it more based on how well it works (Lankton et al., 2015, pp. 884–892). Their study shows that when the type of trust matches how people see the technology, it has a stronger impact on outcomes like enjoyment, usefulness, and willingness to keep using it. This distinction provides a useful foundation for thinking about trust in more advanced technologies. In their study, Lankton et al. compared a more human-like technology (Facebook) to a more system-like one (Microsoft Access) to test how these perceptions influence trust formation and outcomes. However, the next section argues that large language models (LLMs) can exhibit both human-like and system-like characteristics within a single interaction, making the distinction less clear than in Lankton et al.'s original comparison.

2.2 The Dual Nature of Trust in AI

While Lankton et al. originally used their model to compare two different types of technologies, this study applies to AI systems, especially LLMs, which can show both system-like and human-like traits within the same interaction. AI systems are increasingly able to simulate human interaction, especially large language models (LLMs). They show anthropomorphic aspects such as communication, autonomy, learning and adaptation to change, but are also seen as a useful tool for functional tasks, such as retrieving information, automating and navigating (Chen & Park, 2021, p. 2722; Sung et al., 2023, p. 1774). Features such as natural language processing, responsiveness, and personalization blur the boundary between system-like and human-like attributes within one technology (Hsieh & Lee, 2024, p. 619). As Chen and Park (2021, p. 2724) note, such social cues can cause users to perceive AI systems as more intentional or emotionally aware than they actually are. This shifts the foundation of trust from being purely functional to also relational.

It is know from the study by Lankton et al., (2015) that perceived humanness is not an inherent trait of the system, it is established by an individual's expectations, experiences, and focus. Users evaluate AI assistants not only based on their utility, but also on their social presence. Some users focus on competence and reliability; others are more focused on warmth, empathy, or familiarity (Sung et al., 2023, p. 1773). These differences in perception also influence how users form trust AI systems. Two users interacting with the same AI assistant may form different trust relationships based on whether they emphasize the system's tool-like qualities, such as reliability and functionality, or its human-like qualities such as familiarity and integrity. This influences not only their expectations of the system but also how they evaluate its performance, ultimately determining whether they trust the AI

To examine how users form trust relationships with AI systems, this research adopts the theoretical framework of Lankton et al. (2015), which distinguishes between human-like trust and system-like trust. This dual-trust framework is particularly useful because it acknowledges that both forms of trust can coexist, varying in presence based on how human-like the system is perceived to be. The next sections will explore these two forms of trust in greater detail, laying the theoretical foundation for this study.

2.3 Human-like Trust Dimensions

This section explores the specific dimensions of human-like trust that can be applied when users perceive AI systems as social entities. These dimensions illustrate how users may draw on interpersonal trust mechanisms when interacting with AI systems that display human-like qualities.

Lankton et al. (2015) describe Human-Like Trust (HLT) as a reflective second-order construct composed of three interpersonal dimensions: reliability, integrity, and benevolence. In this study, one of the original HLT dimensions is replaced to better fit the context of using an AI assistant, allowing for a more accurate representation of how users perceive social and interpersonal attributes in AI.

First, integrity refers to the perceived honesty and fairness in a technology's actions. When applied to Large Language Models, integrity refers to users' beliefs that the system provides unbiased information and adheres to ethical principles in its responses (Lankton et al., 2015, p. 882). For example, users might trust that an AI assistant is not misleading them or withholding important information. This dimension draws from the traditional human trust concept that others will adhere to acceptable moral principles (Mayer et al., 1995).

Second, competence concerns users' beliefs about the technology, its skills and capabilities to perform effectively within its domain (Lankton et al., 2015, p. 882). In the context of LLMs, users might assess competence through the quality, accuracy, and relevance of responses to complex requests. This parallels the human trust assessment of whether someone possesses the skills and characteristics needed to have influence in a specific domain (McKnight et al., 2002).

Lastly, familiarity reflects the degree to which users feel acquainted with and understand the LLM based on previous interactions and experiences (Gefen et al., 2003). This dimension captures how users' prior experience forms their trust in the system, fostering a sense of comfort and assurance when engaging with the technology.

While Lankton et al. (2015, p. 882) originally included benevolence as part of the human-like trust construct, referring to the belief that the technology has good intentions and acts in the user's interest, this study adopts familiarity instead. This decision is based on the framework proposed by Califf et al. (2020), who conceptualize human-like trust in technology in terms of familiarity, integrity, and competence. Unlike benevolence, familiarity does not rely on the attribution of emotional intent or moral agency, which makes it more fitting for systems like large language models (LLMs). In the context of LLMs, trust is more likely to develop through repeated use and an increasing understanding of how the system behaves, rather than through the perception that it is acting in the user's best interest (Afroogh et al., 2024, p. 4). Familiarity is also related to the reduction of social uncertainty, which has been shown to play an important role in trust development in human–technology interaction (Gefen et al., 2003). Over time, users may come to trust an LLM not because they believe it is well-intentioned, but because they know what to expect from it. This view is supported by Afroogh et al. (2024, p. 4), who argue that benevolence and honesty are less applicable to AI systems precisely because they lack intentionality, which is one of the foundations of interpersonal trust. Instead, trust in AI tends to rely more on perceptions of competence and predictability.

By using the dimensions proposed by Lankton et al. (2015) and Califf et al. (2020), this study follows a human-like trust conceptualization that emphasizes user experience and cognitive evaluation, rather than emotional or moral judgements. Familiarity, along with integrity and competence, forms the basis of the human-like trust construct in this study. They will be examined alongside system-like trust dimensions to develop a comprehensive understanding of trust formation in AI systems that display varying degrees of humanness.

2.4 System-like trust dimensions

This section outlines the key dimensions of system-like trust, which reflect how users evaluate the technical qualities of an AI system as a functional tool. Unlike human-like trust, which involves interpersonal cues, system-like trust is rooted in users' perceptions of the system, its performance, reliability, and utility in helping them achieve specific goals. System-Like Trust (SLT), as conceptualized by Lankton et al. (2015), is a reflective second-order construct consisting of three dimensions: reliability, functionality, and helpfulness. These dimensions reflect users' evaluations of the AI system's technical qualities as a functional tool. For this study, an additional dimension is added to the original SLT framework to create a more comprehensive understanding of user trust in the AI's performance and utility.

First, reliability refers to a technology's consistent performance over time. For LLMs, reliability might be assessed through the consistency of response quality and availability of the service (Lankton et al., 2015, p. 882). Users develop trust when they can depend on the technology to function as expected across multiple interactions without unexpected failures or inconsistencies. McKnight et al. (2011) note that reliability parallels the human trust dimension of integrity but focuses on operational consistency rather than ethical consistency.

Functionality addresses the system's capabilities and features that enable it to perform required tasks (Lankton et al., 2015, p. 882). In LLMs, functionality might include the range of topics it can address, the complexity of queries it can process, and the formats in which it can present information. This dimension focuses on whether the technology has the necessary capabilities to meet user needs, like how we assess human competence but focused on technical rather than learned capabilities.

Helpfulness concerns how responsive the technology is to user needs and how well it helps. For LLMs, this might include how effectively the system adapts to clarification requests, provides additional information when needed, or guides users through complex processes.

Lastly, this study adds privacy and security as an extra dimension to system-like trust. Privacy and security represent users' confidence that the technology will protect their data and interactions. This dimension has been widely acknowledged in the literature as being an important factor to the formation of trust in AI, given increasing concerns about data privacy in AI applications (Afroogh et al., 2024, p. 11). Users need assurance that their requests, personal information, and interaction histories are managed securely and used appropriately (Chen & Park, 2021, p. 2723).

These four dimensions, reliability, functionality, helpfulness, and privacy/security, showcase how users evaluate LLMs as technical systems designed to support goal-oriented tasks. They reflect a form of trust based on performance and operational consistency, rather than social or emotional cues. In this study, system-like trust is examined alongside human-like trust to offer a more complete understanding of how users form trust in AI systems that combine functional utility with human-like interaction.

2.5 Outcomes of Trust Formation

Building on Lankton et al.'s (2015) framework, this study investigates how the two types of trust, human-like and system-like, influence four key user outcomes that determine technology adoption and continued use. These outcomes reflect the functional value and enjoyment users associate with the technology, as well as their willingness to rely on it and maintain engagement over time.

Perceived usefulness refers to the extent to which users believe the AI system enhances their task performance or productivity (Califf et al., 2020, p. 4). It addresses the utilitarian value users associate with the technology, particularly in contexts where efficiency, accuracy, and task support are important. In the context of LLMs, this may involve how well the system supports information retrieval, drafting texts, or automating repetitive tasks. A high level of perceived usefulness often indicates that users view the AI as a valuable tool in their work or daily routines (Sung et al., 2023, p. 1774).

Perceived enjoyment reflects the hedonic value users derive from interacting with the AI system, regardless of whether it improves performance outcomes (Califf et al., 2020, p. 4) . This dimension acknowledges that users may also engage with AI technologies for pleasure, curiosity, or novelty. Especially in personal or creative contexts, enjoyment can play a critical role in user satisfaction and willingness to continue interacting with the system (Lankton et al., 2015, p. 889). While perceived usefulness emphasizes functional benefits, perceived enjoyment highlights the affective dimension of the user experience.

Trusting intention is defined believing the technology has the qualities they need to be able to trust and rely on it later on (Lankton et al., 2015, p. 888). It addresses the degree to which users are comfortable delegating tasks to the technology. In the context of LLMs, this may include trusting the system to provide accurate recommendations, generate important content, or support decision-making processes (Afroogh et al., 2024, p. 2). Trusting intention bridges the gap between users' trust beliefs and their readiness to act on them (Lankton et al., 2015, p. 888).

Continuance intention refers to users' intention to keep using the AI system over time. While this term does not directly represent actual continued use, it has been shown to be a significant predictor of real continuance behavior (Califf et al., 2020, p. 4). When trust is maintained over time, users are more likely to integrate the system into their routines and develop long-term reliance (Lankton et al., 2015, p. 889). As such, it is a meaningful indicator of long-term user engagement and successful technology adoption.

Analyzing the influence of human-like and system-like trust on these outcomes provides an understanding for how different trust dimensions influence users' decisions to adopt and continue using AI systems. The following section expands on these insights by discussing contextual factors that might influence trust formation in AI systems.

2.6 The Moderating Effect of Context on Trust Formation

This study further considers the role of context in forming trust in AI assistants, suggesting that trust formation is influenced not only by the system's perceived humanness and specific trust dimensions but also by the context in which the interaction takes place. Context can play a moderating role because it affects the user's goals for using technology and influences which trusting beliefs, human-like or system-like, are more relevant or prominent (Califf et al., 2020, p. 4; Lankton et al., 2015, p. 884).

Drawing on Social Cognitive Theory (Bandura, 1986; Califf et al., 2020, p. 4) and Affordance Theory (Gibson, 1977), this study recognizes that trust does not develop in isolation. Instead, it emerges from the interaction between the user, the features of the technology, and the environment in which it is used. Social Cognitive Theory suggests that behavior is formed by the continuous interaction between personal factors, such as experiences or attitudes, environmental factors, such as context or setting, and behavior itself, a process known as reciprocal determinism (Bandura, 1986; Califf et al., 2020). In the case of LLMs, this means that trust is formed not only by the technology's capabilities or perceived intentions but also by situational goals, social expectations, and the demands or risks present in the specific environment. For example, Abdul-Rahman and Hailes (2000) illustrate how a mother may develop strong trust in her car mechanic when it comes to vehicle repairs, yet that same trust does not extend to contexts requiring different competencies, such as babysitting. This example shows how trust is not a universal judgment but rather formed by the specific situation and the perceived relevance of the trustee's abilities.

Recent research by Sung et al. (2023) demonstrates that task type significantly influences how users perceive and evaluate AI assistants. When interacting with voice assistants in functional tasks, users reported higher levels of perceived competence, which in turn increased trust and positive attitudes. In contrast, during social tasks, users perceived slightly more warmth, but this did not significantly affect trust or evaluations. These findings suggest that users attend to different attributes of the same AI system depending on the task at hand, underscoring the influence of context on which trust dimensions, such as competence or warmth, are present.

This context-sensitive perception of technology can be understood through the lens of Affordance Theory (Gibson, 1977), which proposes that technologies are interpreted in terms of the action possibilities they offer within a particular environment. Users do not perceive technologies in a vacuum but interpret their utility based on what they are trying to achieve in that given moment. Task type can act as a cue that frames both user goals and the perceived capabilities of the AI, which influences trust formation. (Sung et al., 2023, pp. 1773-1774) For example, in fields like healthcare, manufacturing, and finance, people expect AI to be safe and accurate, qualities that are essential when mistakes can have serious consequences (Afroogh et al., 2024, p. 2). As Chen and Park (2024, pp. 2732-2733) mention, people generally do not seem to place high expectations on chatbot consults in daily usage at home, whereas they do in professional settings where the services are related to financial or other risky decisions. In these professional settings, trust is built on the system's technical performance and reliability, since users depend on the technology to support high-stake decisions and processes. In contrast, personal contexts often involve open-ended or exploratory interactions, such as casual conversation, creative support, or daily planning, where the need for precision or safety is less critical (Sung et al., 2023, pp. 1773-1777). In these situations, users may engage with AI more as a companion or collaborator than as a tool, which can increase the relevance of human-like trust attributes such as integrity, familiarity, and perceived competence for when they use AI.

This study conceptualizes context as a moderating variable that influences the relationship between trust dimensions and key outcomes such as perceived usefulness, enjoyment, trusting intention, and continued use. It is assumed that the technology and the context in which people use it, influence the relevance of human-like and system-like trust dimensions, and that users' perceived relationship with the AI is not fixed but formed by the interaction between individual characteristics, contextual factors, and the humanness perceived in the technology. By integrating context into the trust framework, this research offers a more flexible and complete understanding of how users form trust in AI assistants across different areas of everyday life.

2.7 Hypotheses

Prior research has shown that people can attribute both human-like and system-like trust beliefs when interacting with technology (Lankton et al., 2015, p. 884). However, these relationships may not be consistent across usage contexts. Drawing on Social Cognitive Theory and Affordance Theory (Lankton et al., 2015, pp. 884-886), this study proposes that contextual cues, such as whether an LLM is used in a personal or professional setting, can influence which types of trust beliefs are more relevant to users. Specifically, this study assumes that system-like trust, which is grounded in functional qualities such as reliability, security, and performance, plays a larger role in professional settings. In these contexts, users are more likely to focus on the practical utility of a system, where outcomes like efficiency, data safety, and task support are especially valued (Chen & Park, 2024, pp. 2732–2733). Because work-related tasks often require accuracy and performance, system-like trust beliefs are expected to play a bigger role in forming user evaluations when the AI is used in a work context compared to a personal context. Therefore, the following hypothesis is proposed:

H1: System-like trusting beliefs (reliability, functionality, helpfulness, and privacy/security) will have a stronger influence on a) perceived usefulness, b) perceived enjoyment, c) trusting intention, and d) continuance intention in a work-related context than in a personal context.

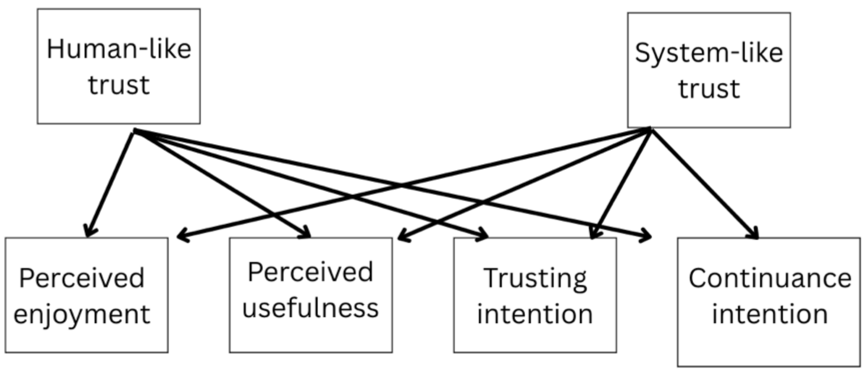
Interactions with AI in a personal context are typically more open-ended and exploratory, focusing less on precision and more on social connection and emotional resonance (Hsieh & Lee, 2024, p. 620). Aligning with such social interactions, human-like trust involves relational dimensions such as competence, integrity, and familiarity (Lankton et al., 2015, p. 889). In personal contexts, users may therefore engage with AI in more casual, relational ways, making social and emotional cues more important (Chen & Park, pp. 2732-2733). As LLMs simulate human-like responses, their perceived warmth and familiarity may matter more in everyday or informal settings, where trust is formed less by functionality and more by interpersonal resonance. Therefore, the following hypothesis is proposed:

H2: Human-like trusting beliefs (integrity, competence, and familiarity) will have a stronger influence on a) perceived usefulness, b) perceived enjoyment, c) trusting intention, and d) continuance intention in a personal context than in a work-related context.

By testing these hypotheses, this study aims to show how the type of trust and the context in which users engage with LLMs together influence how they evaluate and continue using the technology.

Figure 1

Conceptual framework of the study



Chapter 3: Methodology

Chapter 3 outlines the methodological approach used to examine how trust in Large Language Models (LLMs) is influenced by the context in which they are used. This chapter describes the research design, sampling strategy, data collection procedure, measurement instruments, and data analysis.

3.1 Design

This study employs a quantitative research design using a survey methodology to examine the contextual influences on trust in Large Language Models. The research investigates how the context of usage (personal vs. work-related) moderates the relationship between trusting beliefs and key user outcomes. By examining these relationships empirically, this research aims to contribute to an understanding of technology adoption and trust development in the emerging field of generative AI systems. The independent variables are human-like trusting beliefs (integrity, competence, and familiarity) and system-like trusting beliefs (reliability, functionality, helpfulness, and privacy/security). The moderating variable is the usage context, manipulated through participant assignment to one of the two conditions. Dependent variables include perceived usefulness, perceived enjoyment, trusting intention, and continuance intention. All items were measured on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

To ensure construct validity, all measurement items were based on previously validated scales. A reliability analysis was conducted for each construct to assess internal consistency using Cronbach's alpha. Scales with alpha values above .60 were considered reliable. The use of established scales from prior research contributes to both the reliability and validity of the study. Ethical guidelines were followed throughout the study, including an informed consent from all participants and by keeping their information confidential and anonymous, following Erasmus University's guidelines. Participation was completely voluntary, and respondents could stop the survey at any time. To protect privacy, no IP addresses were tracked, all sensitive data was securely stored, and participants' anonymity was fully maintained.

3.2 Sample

This study approached individuals who have used a Large Language Model, such as ChatGPT, Claude, or Copilot, within the last 12 months. A convenience sampling technique was employed to recruit participants through various channels, including professional networks, online platforms, and workplace contacts. Participants were recruited through social media platforms (e.g., LinkedIn, Twitter) and the researcher's professional network. Additionally, snowball sampling was used by asking initial participants to forward the survey to peers who met the eligibility criteria. To ensure sufficient responses, part of the sample was also recruited via Prolific, an online participant recruitment platform, with proof of participant numbers included in Appendix C.

Inclusion criteria required that participants: (1) are at least 18 years old, and (2) have used an LLM within the past 12 months. No restrictions were placed on geographic location, industry sector, or specific role, which allowed for greater generalizability of findings across diverse user populations. No questions were asked regarding gender or age. A minimum sample size of 150 participants was required and met.

3.3 Procedure

Data collection was conducted through a structured online survey using Qualtrics. Upon accessing the survey, participants were presented with an introduction explaining the research purpose, procedures, and how their data would be protected. It was clearly stated that participation was voluntary, responses were anonymous, and participants could withdraw at any time without consequences. After providing informed consent, participants proceeded to the survey.

Two screening questions were then asked to ensure eligibility: (1) whether participants were at least 18 years old, and (2) whether they had used a Large Language Model (LLM) in the past 12 months. Participants who did not meet these criteria were directed to a thank-you page and excluded from further participation.

Eligible participants indicated their primary context of LLM use: personal, work-related, or both equally. Based on this, they were assigned to either the personal or work-related condition. Participants who reported using LLMs equally in both contexts were randomly assigned to one of the two conditions to maintain balanced group sizes. They also reported which LLM they mainly used in the assigned context.

Before starting the main survey items, participants received a context-specific introduction to frame their responses depending on their assigned condition (personal or work-related). The survey then continued with the measurement items for all constructs. To enhance relevance and engagement, the name of the participant's most-used LLM (e.g., ChatGPT, Copilot) was inserted into the wording of all relevant questions. Additionally, a brief reminder of the assigned usage context (personal or work-related) was presented at the start of each question block to maintain consistent interpretation. The average completion time was approximately 8 minutes. The full questionnaire can be found in Appendix B.

3.4 Measures

This study used existing scales to measure human-like and system-like trust, based on the framework by Lankton et al. (2015), but adapted the dimensions slightly to better reflect the context of AI assistants. One dimension, benevolence, was replaced with familiarity in the human-like trust construct, and an additional dimension, privacy and security, was added to the system-like trust construct. These changes were made to align with recent research suggesting that benevolence is less applicable to non-intentional systems (Afroogh et al., 2024, p. 4), and to address for growing user concerns about data protection in AI interactions (Chen & Park, 2021, p. 2723).

3.4.1 Independent variables

The study's primary independent variables were trusting beliefs, divided into two categories: human-like and system-like. Human-like trusting beliefs capture the extent to which users perceive LLMs as having human-like qualities that stimulate trust, and consist of the dimensions of integrity, competence, and familiarity.

The dimension of *integrity* refers to the belief that the LLM adheres to a set of principles that the user finds acceptable (Lankton et al., 2015, p. 882). This is measured with three items, including "The AI-assistant is honest." and "The AI-assistant keeps its commitments when assisting with tasks."

The dimension of *competence* refers to the belief that the LLM has the ability to do what the trustor needs to have done (Lankton et al., 2015, p. 882). This is measured with three items, including "The AI-assistant is competent and effective in performing tasks." and "The AI-assistant is a capable and skilled assistant.".

Familiarity refers to the degree to which a user feels acquainted with and understands the LLM based on previous interactions and experiences (Gefen et al., 2003). This is measured with three items, including "I am familiar with the AI-assistant through using it before." and "I am familiar with the AI-assistant through searching for information or help."

System-like trusting beliefs capture the extent to which users perceive LLMs as reliable and effective technical systems, and consist of the dimensions of reliability, functionality, helpfulness and privacy and security.

The dimension of *reliability* refers to the belief that the LLM operates consistently and dependably (Lankton et al., 2015). This is measured with three items, including "The AI-assistant is a very reliable tool." and "The AI-assistant does not fail me."

Functionality measures the belief that the LLM has the features and capabilities needed to accomplish the user's tasks (Hsu et al., 2014). This is measured with three items, including "The AI-assistant has the functionality I need" and "The AI-assistant has the features required for my tasks."

Helpfulness refers to the belief that the LLM provides assistance that is valuable and beneficial to the user (Lankton et al., 2015). This is measured with three items, including "The AI-assistant provides helpful suggestions" and "The AI-assistant provides whatever help I need."

Privacy and security measures the belief that the LLM protects user data and maintains confidentiality (Hsu et al., 2014). This is measured with three items, including "The AI-assistant ensures that my information is kept secure." and "I feel safe using the AI-assistant when performing tasks."

3.4.2 Dependent variables

The main outcomes of interest were perceived usefulness, perceived enjoyment, trusting intention, and continuance intention, measured using established and frequently used scales from the technology acceptance and trust literature (Lankton et al., 2015, p. 888).

The following outcome variables were measured to assess the impact of trusting beliefs:

Perceived usefulness measures the degree to which a person believes that using the LLM would enhance their performance (Davis, 1989). This is measured with three items, including "Using the AI-assistant improves my performance in tasks" and "The AI-assistant increases my productivity in activities."

Perceived enjoyment refers to the extent to which the activity of using the LLM is perceived to be enjoyable (Davis et al., 1992). This is measured with three items, including "I find using the AI-assistant to be enjoyable." and "I have fun using the AI-assistant."

Trusting intention accounts for the willingness to depend on the LLM in the future (McKnight et al., 2002). This is measured with three items, including "I can always rely on the AI-assistant for challenging tasks." and "I feel I can depend on the AI-assistant when completing tasks."

Continuance intention refers to the user's intention to continue using the LLM in the future (Venkatesh et al., 2003). This is measured with three items, including "I intend to continue using the AI-assistant in the future" and "I predict that I will continue using the AI-assistant."

3.4.3 Moderating variable

The moderating variable in this study is the context of LLM usage, operationalized as either personal or work-related. This variable examines how the setting in which an LLM is used may influence the relationship between trusting beliefs and user outcomes. In the personal context, participants were asked to reflect on their experiences using LLMs for non-professional tasks, such as entertainment, personal projects, or daily life assistance. In the work-related context, participants reflected on their use of LLMs for professional purposes, including workplace communication, coding, document creation, or academic research.

Context was measured as a dichotomous variable (0 = personal context, 1 = work-related context) based on participants' self-reported primary usage pattern. Participants who reported using LLMs equally in both contexts were randomly assigned to one of the two conditions to ensure balanced group sizes.

The survey contained two parallel blocks of items, one framed around personal use and one around work-related use. Each participant only completed one of these blocks based on their assigned context. The wording of the items was identical across conditions. For the analysis, responses from both context conditions were combined into single outcome variables, and the binary context variable was used to examine its moderating effect on the relationships of interest.

3.5 Data analysis

To test Hypotheses 1 and 2, a series of multiple linear regression analyses were conducted to examine whether the effect of trusting beliefs on outcome variables is moderated by the context in which the AI assistant is used (personal vs. work-related). Specifically, interaction terms between trust constructs and context were created and included in the regression models to test for moderation effects.

Prior to the regression analyses, a Principal Component Analysis (PCA) was conducted on all trust-related items to assess the dimensionality of the trust constructs. Two factors were created: human-like trust (HLT), consisting of items measuring integrity, competence, and familiarity; and system-like trust (SLT), consisting of items measuring reliability, functionality, helpfulness, and privacy/security. Following the PCA, composite scores for HLT and SLT were computed by averaging the respective items. The reliability of these constructs was assessed using Cronbach's alpha and composite reliability, with values above .60 considered acceptable.

The moderator variable, context, was dummy-coded (0 = work-related, 1 = personal). All predictor variables (HLT and SLT) were mean centered to reduce multicollinearity with the interaction terms. Interaction terms were then computed by multiplying the centered trust scores with the context variable (HLT × Context and SLT × Context).

Regression analyses were conducted separately for each of the four dependent variables: perceived usefulness, perceived enjoyment, trusting intention, and continuance intention. For each outcome variable, the predictors were entered into the regression model in two steps (blocks). In the first step, the main effects of human-like trust (HLT), system-like trust (SLT), and context were entered. In the second step, the interaction terms between HLT and context, and between SLT and context, were added to the model. The significance of these interaction terms in the second step indicates whether the relationship between trusting beliefs and the outcome variables is moderated by the context, thus providing support for the proposed moderation hypotheses. For each regression model, unstandardized coefficients (B), standard errors, standardized beta values (β), p-values, and 95% confidence intervals were reported.

Chapter 4: Results

This chapter provides an overview of the sample. Next, it assesses the dimensionality and internal consistency of both types of trust (human-like and system-like) and the outcome variables. Because some of the original scales were adapted, principal component analyses (PCA) were conducted to check whether the items and subscales still formed coherent constructs. Lastly, multiple regression analyses were conducted to test the hypotheses. Interaction terms were included between context (personal vs. work) and each type of trust in the regression model.

4.1 Sample characteristics

Of the 150 participants, 60.7% indicated no clear primary usage of a LLM in either a personal or work context and were randomly assigned to a context condition. Among the total sample, 53.3% were placed in the personal context condition and 46.7% in the work context. Additionally, 18.0% of participants explicitly primarily used the AI assistant in a personal context, while 21.3% primarily used it in a work-related context. No demographic information (e.g., age or gender) was collected.

4.2 Psychometric Properties of the Measurement Scales

To assess the dimensionality of the trust constructs, separate analyses were conducted for System-Like Trust (SLT) and Human-Like Trust (HLT). SLT was adapted in this study by adding a new subdimension, security and privacy, to the original structure validated by Lankton et al. (2015), which included reliability, functionality, and helpfulness. Given this adjustment, a Principal Component Analysis (PCA) was conducted to examine whether the four dimensions together form a coherent underlying factor. The suitability of the data for PCA was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity (Bartlett, 1954). Internal consistency and dimensionality were also evaluated for each individual subscale.

HLT was likewise adapted by replacing benevolence with familiarity, based on the framework proposed by Califf et al. (2020). Because this operationalization deviates from Lankton et al.'s (2015) original model, a PCA was also conducted to assess whether competence, integrity, and familiarity together reflect a single latent construct. Factor loadings for both SLT and HLT are presented in Appendix A.

For competence, the KMO value was .75, exceeding the recommended threshold of .60 (Kaiser, 1970), and Bartlett's Test of Sphericity was significant, $\chi^2(3) = 252.69$, $p < .001$, indicating sufficient correlations among the items (Bartlett, 1954). One component was extracted with an eigenvalue above 1, explaining 82.01% of the variance. All items loaded strongly on the component (loadings = .89 to .91), and the internal consistency of the scale was high (Cronbach's $\alpha = .88$).

For integrity, The KMO value was .68, indicating moderate sampling adequacy, and Bartlett's Test of Sphericity was significant, $\chi^2(3) = 160.71$, $p < .001$. One component was extracted, explaining 72.61% of the variance. Factor loadings ranged from .79 to .90. The internal consistency was high (Cronbach's $\alpha = .81$).

For familiarity, the KMO value was .57, slightly below the commonly accepted threshold of .60, indicating marginal sampling adequacy, though Bartlett's Test of Sphericity was significant, $\chi^2(3) = 64.42$, $p < .001$. One component emerged, explaining 56.99% of the variance, with item loadings ranging from .61 to .85. The internal consistency was moderate (Cronbach's $\alpha = .60$).

To assess whether the three constructs (competence, integrity, and familiarity) together form a coherent higher-order factor of Human-Like Trust (HLT), a Principal Component Analysis (PCA) was conducted using the mean scores of each subscale. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .618, which is above the minimum acceptable threshold of .60 (Kaiser, 1970). Bartlett's Test of Sphericity was significant, $\chi^2(3) = 146.36$, $p < .001$, indicating sufficient correlations among the variables (Bartlett, 1954). One component was extracted with an eigenvalue greater than 1, accounting for 68.19% of the total variance. Factor loadings for the three subscales were strong for competence (.894) and integrity (.884), and moderate for familiarity (.681). These results indicate that the three constructs load onto a single underlying factor, justifying the use of this composite HLT score.

For helpfulness, the KMO value was .65, indicating moderate sampling adequacy (Kaiser, 1970), and Bartlett's Test of Sphericity was significant, $\chi^2(3) = 139.19$, $p < .001$, confirming sufficient correlations among the items (Bartlett, 1954). One component was extracted with an eigenvalue above 1, explaining 69.74% of the variance. Factor loadings ranged from .77 to .89. The internal consistency of the scale was moderate (Cronbach's $\alpha = .76$).

For reliability, the KMO value was .72, indicating adequate sampling adequacy, and Bartlett's Test of Sphericity was significant, $\chi^2(3) = 189.67$, $p < .001$. A single component was extracted, accounting for 76.76% of the variance. All items loaded strongly on the component, with loadings ranging from .85 to .90. Internal consistency was high (Cronbach's $\alpha = .85$).

For functionality, the KMO value was .70, indicating moderate sampling adequacy, and Bartlett's Test of Sphericity was significant, $\chi^2(3) = 221.25$, $p < .001$. One component was extracted, explaining 78.13% of the variance. Loadings ranged from .83 to .92. The internal consistency of the scale was high (Cronbach's $\alpha = .86$).

For security and privacy, the KMO value was .73, exceeding the recommended threshold, and Bartlett's Test of Sphericity was significant, $\chi^2(3) = 321.31$, $p < .001$. One component was extracted, accounting for 84.70% of the variance. Factor loadings were high, ranging from .88 to .94. The internal consistency of the scale was high (Cronbach's $\alpha = .90$).

To assess whether the four constructs (reliability, functionality, helpfulness, and privacy/security) together form a coherent higher-order factor of System-Like Trust (SLT), a Principal Component Analysis (PCA) was conducted using the mean scores of each subscale. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .77, exceeding the minimum acceptable threshold of .60 (Kaiser, 1970). Bartlett's Test of Sphericity was significant, $\chi^2(6) = 186.90$, $p < .001$, indicating sufficient correlations among the variables (Bartlett, 1954). One component was extracted with an eigenvalue greater than 1, accounting for 62.73% of the total variance. Factor loadings were strong for reliability (.86), functionality (.80), and helpfulness (.80), and moderate for privacy/security (.70). These results indicate that the four constructs load onto a single underlying factor, justifying the use of a composite SLT score.

A Principal Component Analysis (PCA) was conducted for each outcome variable to assess one-dimensionality and internal consistency.

For perceived enjoyment, the KMO value was .74, indicating moderate sampling adequacy, and Bartlett's Test of Sphericity was significant, $\chi^2(3) = 295.01$, $p < .001$. Items loaded in one component, explaining 85.54% of the variance. Factor loadings ranged from .90 to .94, and Cronbach's alpha was .90, indicating high internal consistency.

For perceived usefulness, a single component was also extracted, explaining 80.62% of the variance. The KMO value was .73, and Bartlett's Test of Sphericity was significant, $\chi^2(3) = 236.01$, $p < .001$. Factor loadings ranged from .87 to .92, and Cronbach's alpha was .88. For trusting intention, PCA extracted one component explaining 76.78% of the variance. The KMO value was .72, and Bartlett's Test of Sphericity was significant, $\chi^2(3) =$

189.41, $p < .001$. Item loadings ranged from .85 to .89, and Cronbach's alpha was .85, indicating good reliability.

Finally, the PCA for continuance intention revealed one component that accounted for 90.22% of the variance. The KMO value was .77, and Bartlett's Test of Sphericity was significant, $\chi^2(3) = 422.40$, $p < .001$. Factor loadings were high, ranging from .94 to .96, and Cronbach's alpha was .95, reflecting high internal consistency. These results confirm that all outcome measures reflect unidimensional constructs with strong internal reliability.

Table 4.1 reports the correlations, means, and standard deviations for all variables.

Table 4.1

Descriptive Statistics and Correlations (n = 150).

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*M*	*SD*
1. Integrity	—														5.10	1.10
2. Competence	.74**	—													5.67	0.91
3. Familiarity	.39**	.41**	—												5.72	0.92
4. Reliability	.65**	.67**	.33**	—											4.66	1.29
5. Functionality	.56**	.71**	.42**	.57**	—										5.31	1.04
6. Helpfulness	.54**	.56**	.30**	.61**	.54**	—									5.52	0.99
7. Privacy/Security	.39**	.42**	.27**	.47**	.45**	.49**	—								4.11	1.47
8. Perceived Usefulness	.41**	.54**	.32**	.50**	.60**	.51**	.45**	—							5.70	1.00
9. Perceived Enjoyment	.36**	.44**	.26**	.53**	.57**	.57**	.36**	.54**	—						5.69	0.95
10. Trusting Intention	.52**	.58**	.31**	.67**	.62**	.54**	.46**	.59**	.60**	—					4.77	1.26
11. Continuance Intention	.49**	.54**	.41**	.51**	.55**	.56**	.44**	.57**	.49**	.45**	—				6.00	0.99
12. Context	-.06	-.07	-.11	-.10	-.02	-.06	.11	.10	-.08	-.09	.07	—			0.47	0.50
13. HLT	.88**	.87**	.71**	.68**	.58**	.67**	.53**	.51**	.43**	.57**	.58**	-.09	—		5.50	0.80
14. SLT	.71**	.75**	.44**	.85**	.76**	.76**	.77**	.63**	.55**	.74**	.62**	-.01	.77**	—	4.90	0.95

Note. Context coded as 0 = personal, 1 = work. **p ≤ .001 (2-tailed).

4.3 Hypothesis testing

To examine whether context (work-related vs. personal) moderated the relationship between system-like and human-like trusting beliefs and perceived usefulness, a hierarchical multiple regression analysis was conducted using a two-step approach. In the first step, system-like trust, human-like trust, and context were entered as predictors. In the second step, interaction terms between context and each type of trusting belief were added to test for moderation effects according to the hypotheses.

The addition of the interaction terms in the second step led to a small increase in explained variance ($\Delta R^2 = .03$), but the F-change statistic showed this increase was not statistically significant. Therefore, the interaction effects were not supported. These results do not support Hypothesis 1a, which predicted a stronger influence of system-like trusting beliefs on perceived usefulness in the work context, nor Hypothesis 2a, which predicted a stronger influence of human-like trusting beliefs in the personal context.

In the first step, the model was statistically significant and explained approximately 39.4% of the variance in perceived usefulness ($R^2 = .41$, $F(3, 146) = 33.32$, $p < .001$). System-like trusting beliefs were positively associated with perceived usefulness ($\beta = .55$, $p < .001$). Human-like trusting beliefs and context were positively related to perceived usefulness, but these associations were not significant.

Table 4.2

Results of the hierarchical moderated regression analyses predicting perceived usefulness

Independent variables	Steps	
	1	2
Main effects		
System-like trusting beliefs (SLT)	.55**	.65**
Human-like trusting beliefs (HLT)	.10	.16
Context (0 = work-related, 1 = personal)	.11*	.12*
Moderating effects		
SLT × Context		-.21
HLT × Context		-.01

Independent variables	Steps	
R^2	.41	.43
F-statistic	33.32**	21.92**
R^2 change	.41	.03
F-change statistic	33.32	3.27

N = 150.

Note. *p < .10. **p < .001. Standardized coefficients are reported.

A similar hierarchical multiple regression analysis was conducted to investigate whether context moderated the relationship between system-like and human-like trusting beliefs and perceived enjoyment. Again, a two-step approach was used.

The addition of the interaction terms in the second step led to a small increase in explained variance ($\Delta R^2 = .017$), but the F-change statistic was not statistically significant. The interaction effects were not supported. These findings do not support Hypothesis 1b, which predicted that system-like trusting beliefs would have a stronger influence on perceived enjoyment in the work-related context compared to the personal context. Similarly, Hypothesis 2b, which expected a stronger influence of human-like trusting beliefs on perceived enjoyment in the personal context, was not supported.

In the first step, the model was statistically significant and explained approximately 31.0% of the variance in perceived enjoyment ($R^2 = .31$, $F(3, 146) = 21.85$, $p < .001$). System-like trusting beliefs were positively associated with perceived enjoyment ($\beta = .56$, $p < .001$). Human-like trusting beliefs and context were positively related to perceived enjoyment, but these associations did not reach statistical significance.

Table 4.3

Results of the hierarchical moderated regression analyses predicting perceived enjoyment

Independent variables	Steps	
	1	2
Main effects		
System-like trusting beliefs (SLT)	.56*	.68*
Human-like trusting beliefs (HLT)	-.01	-.05

Independent variables	Steps	
Context (0 = work-related, 1 = personal)	-.10	-.07
Moderating effects		
SLT × Context		-.26
HLT × Context		.14
R^2	.31	.33
F-statistic	21.85*	14.01*
R^2 change	.41	.02
F-change statistic	21.85*	1.85

N = 150.

Note. *p < .001. Standardized coefficients are reported.

A third hierarchical multiple regression analysis was conducted to examine whether context moderated the relationship between system-like and human-like trusting beliefs and trusting intention. The analysis followed the same two-step structure as the previous models.

The addition of the interaction terms in step two led to a small increase in explained variance ($\Delta R^2 = .013$), but the F-change statistic indicated that this increase was not statistically significant. These findings do not support Hypothesis 1c, which predicted that system-like trusting beliefs would have a stronger influence on trusting intention in the work-related context compared to the personal context. Similarly, Hypothesis 2c, which expected a stronger influence of human-like trusting beliefs in the personal context, was not supported.

In the first step, the model was statistically significant and explained approximately 55.0% of the variance in trusting intention ($R^2 = .55$, $F(3, 146) = 59.51$, $p < .001$). System-like trusting beliefs had a significant positive association with trusting intention ($\beta = .74$, $p < .001$). Human-like trusting beliefs and context were not significantly associated with trusting intention.

Table 4.4

Results of the hierarchical moderated regression analyses predicting trusting intention

Independent variables	Steps	
	1	2
Main effects		
System-like trusting beliefs (SLT)	.74**	.61**
Human-like trusting beliefs (HLT)	-.01	.10
Context (0 = work-related, 1 = personal)	-.08	-.09
Moderating effects		
SLT × Context		.25*
HLT × Context		-.22
R^2	.55	.56
F-statistic	59.51**	26.67**
R^2 change	.55	.01
F-change statistic	59.51**	2.09

N = 150.

Note. *p < .05 **p < .001. Standardized coefficients are reported.

To examine whether context (work-related vs. personal) moderated the relationship between system-like and human-like trusting beliefs and continuance intention, a hierarchical multiple regression analysis was conducted using a two-step approach.

Model 2 shows that the interaction between SLT and context was significant (β = –.36, p = .008), indicating that the relationship between SLT and continuance intention differs depending on context. Figure 4.1 visualizes the interaction between SLT and context. Post hoc probing of the simple slopes (Aiken & West, 1991) indicated that SLT was a significant positive predictor of continuance intention in the personal context (b = 0.63, t = 4.46, p < .001) but showed no significant effect in the work context (b = 0.05, t = 0,29 p = .77). This finding does not support Hypothesis 1d, which predicted a stronger positive effect of SLT on continuance intention in the work-related context.

The interaction between HLT and context was also significant (β = .43, p < .05), indicating that the relationship between HLT and continuance intention differed by context. Figure 4.2 visualizes the interaction between HLT and context. Post hoc probing of the simple slopes (Aiken & West, 1991) revealed that HLT was a significant positive predictor of continuance intention in the work context ($b = 0.74$, $t = 4.27$, $p < .001$) but showed no significant effect in the personal context ($b = 0.03$, $t = 0.17$ $p = .863$). This finding does not support Hypothesis 2d, which predicted a stronger positive effect of HLT on continuance intention in the personal context.

Model 1, which included the main effects of SLT, HLT, and context, was statistically significant and explained 41.8% of the variance in continuance intention ($R^2 = .42$, $F(3, 146) = 34.93$, $p < .001$). Both SLT ($\beta = .40$, $p < .001$) and HLT ($\beta = .28$, $p = .006$) were significant positive predictors. Context was not a significant predictor.

Table 4.5

Results of the hierarchical moderated regression analyses predicting continuance intention

Independent variables	Steps	
	1	2
Main effects		
System-like trusting beliefs (SLT)	.40**	.61**
Human-like trusting beliefs (HLT)	.28*	.03
Context (0 = work-related, 1 = personal)	.10	.11
Moderating effects		
SLT × Context		-.36*
HLT × Context		.43*
R^2	.42	.45
F-statistic	34.93**	13.15**
R^2 change	.42	.03
F-change statistic	34.93**	4.30*

N = 150.

Note. *p < .05. **p < .001. Standardized coefficients are reported.

Figure 4.1

Interaction Effect of System-Like Trust and Context on Continuance Intention.

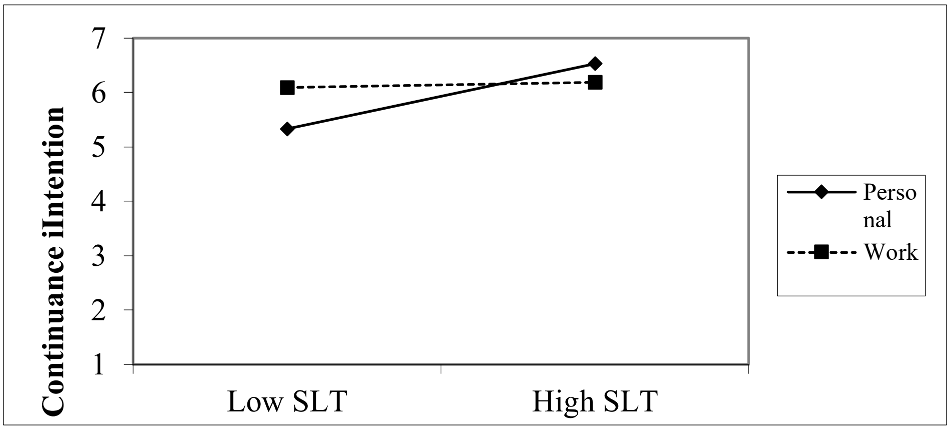
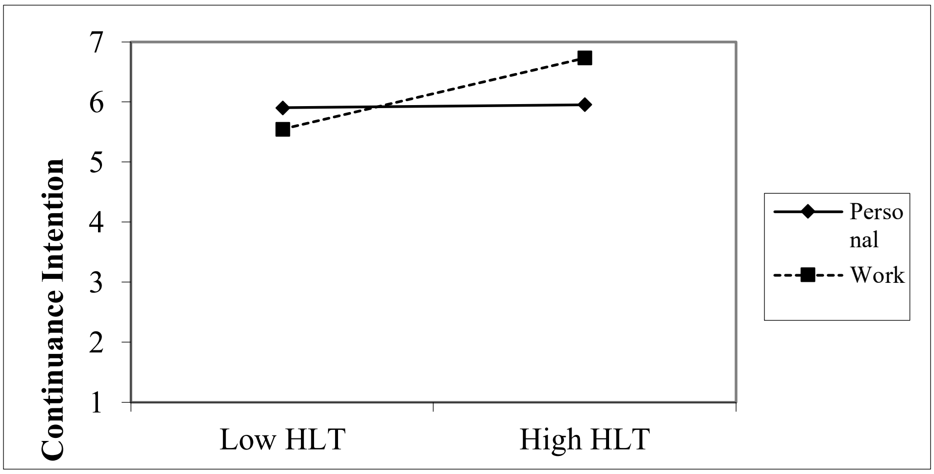


Figure 4.2

Interaction Effect of Human-Like Trust and Context on Continuance Intention.



Among the four dependent variables, only continuance intention showed significant interactions with context. Specifically, significant interaction effects were observed for both system-like trusting beliefs (SLT) and human-like trusting beliefs (HLT). SLT showed a significant effect in the personal context, whereas HLT only had a significant effect in the work context. No significant interaction effects were found for perceived usefulness, perceived enjoyment, or trusting intention. System-like trusting beliefs were significant predictors of all four outcomes, whereas human-like trusting beliefs was only found to be significant predictor for continuance intention.

In sum, the findings do not support Hypothesis 1, as SLT had a stronger effect in the personal rather than work context for continuance intention, contrary to the prediction. Hypothesis 2 is also not supported, since HLT only had a significant effect in the work context and only for continuance intention, rather than showing stronger effects in the personal context as hypothesized.

Chapter 5: Discussion and Implications

This study aimed to answer the following research question: How do human-like and system-like trusting beliefs influence user outcomes (perceived usefulness, perceived enjoyment, trusting intention, and continuance intention) in the use of Large Language Models, and how is this relationship moderated by the context of use (personal vs. work-related)? Building on the dual trust framework proposed by Lankton et al. (2015), which suggests that users apply different trust models depending on whether they perceive a technology as more human-like or system-like, this study examined these dimensions in the context of LLMs, technologies that blend human-like and system-like attributes. Specifically, the research investigated how human-like trusting beliefs (integrity, competence, and familiarity) and system-like trusting beliefs (reliability, functionality, helpfulness, and privacy/security) relate to user outcomes and how these relationships differ between personal and professional contexts.

Regarding H1, system-like trusting beliefs were significant positive predictors of all four outcomes: perceived usefulness, perceived enjoyment, trusting intention, and continuance intention. However, contrary to the hypothesis, the moderation analysis showed that SLT did not have a significantly stronger effect in work contexts for any of these outcomes. In fact, the only significant interaction involving SLT indicated the opposite: system-like trusting beliefs had a significantly stronger influence on continuance intention in personal contexts. This finding suggests that although people consistently rely on system-related characteristics, such as reliability and helpfulness, when evaluating LLMs, their role becomes even more important when users consider whether they will continue using the LLM in their personal life. This is opposite from the initial assumption that system-like beliefs would primarily drive use in more utilitarian, work-related settings.

Regarding H2, human-like trusting beliefs were only positively associated with continuance intention. Context did moderate the relationship between HLT and continuance intention, but in the opposite direction of what was predicted. That is, human-like trusting beliefs had a significantly stronger influence on continuance intention in work contexts, rather than in personal contexts as hypothesized. While this is not in line with H2, it does show an unexpected role of human-like qualities in forming longer-term intentions to use LLMs at work. These results may indicate that when people consider whether to continue integrating LLMs into their work environment, they rely on the LLM's sense of integrity, competence, and familiarity, traits often related to interpersonal relationships. The hypothesized greater relevance of HLT in personal settings was not supported by any significant interaction effects for any of the outcomes.

5.1 Theoretical Implications

The results of this study contribute to theory in several ways. First, they reinforce the conceptual distinction between system-like and human-like trust proposed by Lankton et al. (2015), demonstrating that these are not opposing but coexisting dimensions of trust in AI systems. System-like trust, in particular, emerged as a consistent predictor across all outcome variables. This suggests that users primarily evaluate LLMs through a functional lens, focusing on attributes such as reliability, helpfulness, and security. At the same time, the results show that human-like trusting beliefs still contribute to the outcome of continuance intention, indicating that relational aspects of trust may become more relevant over time or in certain usage contexts. This supports a multidimensional understanding of trust in AI by recognizing that both functional aspects and human-like qualities influence how users experience and respond to these systems.

Second, this study provides some support that context can influence how users form trust in AI assistants, particularly regarding continuance intention. Drawing on Affordance Theory (Gibson, 1977) and Social Cognitive Theory (Bandura, 1986), this study proposed that context moderates the relationship between trusting beliefs and user outcomes. Although the moderation effects were not significant across all models, they did reach significance for continuance intention. In a work context, human-like trusting beliefs were a stronger predictor of continued use, whereas in a personal context, system-like trusting beliefs had more influence. Although this contradicts our initial expectations, it indicates that the relevance of trust dimensions may shift depending on the setting. This suggests that users may prioritize different trust dimensions depending on whether they use an LLM in a professional or personal context. This aligns with prior research by Chen and Park (2021, p. 2733) and Afroogh et al. (2024, p. 11), who emphasize that trust formation in AI is formed by situational factors and the perceived role of the technology. However, the relatively limited scope of significant moderation effects calls for further research to investigate under what conditions context forms trust in AI.

Third, the relatively weak effects of human-like trust on the outcome variables suggest that while competence, helpfulness and familiarity may support continued engagement, they are not necessarily sufficient to drive trusting intention, enjoyment, or perceived usefulness. This indicates that users may prioritize performance and reliability over relational qualities, particularly when interacting with AI assistants that lack genuine emotions or intentions.

Supporting this, Afroogh et al. (2024, p. 4) argue that, unlike interpersonal trust, which involves perceptions of benevolence, integrity, and intentionality, trust in AI is primarily formed by perceptions of ability, given that AI systems do not possess true agency or social presence. Accordingly, users may place more weight on system-level attributes such as performance, predictability, and functionality when evaluating AI technologies.

Since AI systems only simulate social presence and lack genuine human intentionality, much of the literature has focused on understanding the role and limits of anthropomorphism in AI design. For instance, Chen and Park (2021, p. 2732) found that while anthropomorphic cues in intelligent personal assistants can increase perceptions of warmth and personality, they do not consistently lead to higher trust or stronger usage intentions, particularly when users are aware that the system lacks true intentionality. Similarly, Hsieh and Lee (2024, p. 620) mention that excessive anthropomorphic design can create unrealistic expectations, sometimes resulting in confusion or even a sense of uncanniness. Together, these studies suggest that while social cues can enhance user engagement, they do not automatically foster trust. Rather, they suggest that social features may boost emotional connection, but without functional credibility, trust may fade over time. A balanced design that integrates both social presence and reliable functionality is therefore necessary for creating lasting engagement and trust in AI systems (Hsieh & Lee, 2024, p. 626).

Lastly, the finding that SLT was more predictive in personal contexts for continuance intention challenges the initial expectation. It suggests that users may also value functionality and reliability in informal settings, particularly when LLMs are used for tasks that require precision, such as planning or summarizing personal information. Although this study did not explicitly examine task characteristics, this may indicate that users' interpretations of a task's demand, rather than using a LLM in a specific context labelled "personal" or "professional", influence which trust dimension becomes more relevant. Other studies support this view and have researched the effect of task type on forming trust in technologies. For example, Sung et al. (2023, pp. 1782-1783) found that task features such as complexity and risk can influence how people build trust in voice assistants. Their study also shows that functional tasks lead to more positive user attitudes through perceptions of competence, while social tasks, although associated with warmth, do not necessarily increase trust or positive attitudes. This aligns with our findings that system-like trust was a significant predictor across all outcome variables, emphasizing how users prioritize functionality and reliability when evaluating LLMs, regardless of context. It also raises the idea that when users handle personal or sensitive information, concerns about privacy might make them prioritize reliability and control which are key aspects of system-like trust. Research by Afroogh et al. (2024, p. 11) underscores this tradeoff: higher privacy concerns often lead to lower trust because people want control over how their personal data is shared and used. When users feel they lack control, they may be more cautious and put more weight on whether the AI system reliably protects their information. This suggests that in personal contexts, trust might hinge not just on how human-like an AI seems, but also on how well it handles privacy and data protection. This is an area that can be explored further in future research.

5.2 Practical Implications

From a practical perspective, this study offers several implications for developers, designers, and organizations using LLMs. First, enhancing system-like trust should be considered a priority. Across all outcomes, SLT emerged as the most influential predictor, suggesting that users need to feel the system is functional, reliable, and secure before they are willing to rely on it. As Afroogh et al. (2024) suggest, because AI systems lack intentionality and therefore cannot exhibit interpersonal traits like benevolence, trust in AI relies heavily on users' perceptions of the system's competence, predictability, and technical quality. Developers can focus on these aspects by providing clear cues about the LLM's performance, such as consistency in outputs or responsiveness to complex tasks, can help reinforce system-like trust. Similarly, communicating how user data is protected can support trust, particularly in environments where privacy and security are essential (Chen & Park, 2021, p. 2723).

Second, human-like attributes still play a role, particularly for long-term use in work settings. Features that support familiarity, such as personalized prompts or remembering user preferences, could help foster relational trust over time. However, as previous literature discussed, over-anthropomorphizing may not increase trust and could cause negative emotions or even uncanniness (Hsieh & Lee, 2024, p. 620). Despite this opposition, as technology advances, AI assistants are becoming increasingly human-like in appearance and behavior. This shift makes it important to study how characteristics like humanness, competence, and warmth influence user responses (Sung et al., 2023, p. 1784).

5.3 Limitations and Suggestions for Future Research

There are several limitations that should be acknowledged with this study. First, the study relied on self-reported data collected through a survey. While this method is appropriate for measuring perceptions and intentions, it cannot establish causal relationships. Future research could build on these findings using experimental designs or field studies to test how trust in AI evolves over time and in real-world usage.

Second, the use of a survey design with assigned usage contexts may have limited the clarity of contextual influence. Although participants were asked to reflect on either personal or work-related use, some may not have clearly separated these settings in their responses. Even though reminders were provided at the start of each question block, it is possible that participants still considered elements of both contexts. Future research could explore more specific, task-based situations or examine how trust changes when people switch between contexts in real time.

While this study focused on LLMs as a general category, participants selected a specific LLM to reflect on after being assigned to a context. As a result, differences in interface or capabilities, such as those between ChatGPT and Microsoft Copilot, may have influenced their trust perceptions. Additionally, research on other AI assistants, such as voice-based systems that often feel more human due to natural language interaction (Afroogh et al., 2024, p. 9), or specialized tools for tasks such as software development and online shopping (Svenningsson & Faraon, 2019, p. 151), shows that trust dynamics can vary based on the AI's nature and how it is presented. Future research could examine whether the observed relationships hold across different LLMs or whether specific design features form trust in distinct ways.

This study did not explicitly account for cultural differences or varying levels of usage experience, both of which may influence trust in LLMs. Trust perceptions, particularly regarding privacy, reliability, and expectations of technological behavior, can differ significantly across cultural contexts. Different cultures have unique protocols, standards, and laws that influence what is considered acceptable or trustworthy behavior in technology (Afroogh et al., 2024, p. 22). AI systems need to have flexibility to adapt within these cultural boundaries, which can be informed by data collected through questionnaires, interviews, and surveys. A more geographically and culturally diverse sample could provide deeper insight into whether the trust dimensions identified here are broadly applicable or influenced by cultural norms. Additionally, participants with more experience with technology may have evaluated the LLMs differently from those with less familiarity, as prior experience has been found to be a significant factor influencing people' s trustworthiness evaluation towards human-robot interaction (Afroogh et al., 2024, p. 9). Future research could examine how both cultural background and digital experience influence the formation of trust in AI systems.

In conclusion, this study adds to the understanding of how trust in Large Language Models (LLMs) is formed and influenced by both the perceived features of the technology and the context in which it is used. By distinguishing between human-like and system-like trusting beliefs, and examining their effects on user outcomes, the study shows that these trusting dimensions operate differently and have different levels of influence. System-like trust emerged as the most consistent predictor across outcomes, while human-like trust played a more selective role, particularly in supporting continued use. Moreover, the findings offer initial evidence that context moderates these relationships, but only for continuance intention, suggesting part of trust formation is influenced by situational factors. The insights contribute to a more nuanced. view of trust in AI systems, one that acknowledges the dual nature of LLMs as both tools and social agents. As LLMs continue to integrate into diverse areas of daily and professional life, understanding how different trusting beliefs interact with user goals and environments becomes important for effective design and implementation. Future research should build on these findings by investigating trust formation over time, across cultures, and in real-world settings to further develop theory and guide responsible AI usage.

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Appendix A: Measures, factor loadings, and Cronbach alphas

Constructs	Item	Factor loadings
Competence	(α = .89)	
	(1=strongly disagree, 7= strongly agree)	
	1. The AI-assistant is competent and effective in performing tasks.	.91
	2. The AI-assistant performs its role of assisting with tasks very well.	.91
	3. The AI-assistant is a capable and skilled assistant.	.89
	(α = .81)	
Integrity	(1=strongly disagree, 7= strongly agree)	
	1. The AI-assistant is truthful in its responses and actions.	.81
	2. The AI-assistant is honest.	.74
	3. The AI-assistant keeps its commitments.	.63
Familiarity	(α = .60)	
	(1=strongly disagree, 7= strongly agree)	
	1. I am familiar with the AI-assistant through using it before.	.85
	2. I am familiar with the AI-assistant through interacting with it.	.61
	3. I am familiar with the AI-assistant through searching for information.	.79
Helpfulness	(α = .76)	
	(1=strongly disagree, 7= strongly agree)	
	1. The AI-assistant provides helpful suggestions.	.84
	2. The AI-assistant offers guidance when needed to improve task completion.	.89
	3. The AI-assistant provides whatever help I need.	.77
Reliability	(α = .85)	
	(1=strongly disagree, 7= strongly agree)	

Constructs	Item	Factor loadings
	1. The AI-assistant is a very reliable tool. 2. The AI-assistant does not fail me. 3. The AI-assistant consistently works as expected.	.88 .90 .85
Functionality	(α = .86) (1=strongly disagree, 7= strongly agree) 1. The AI-assistant has the functionality I need. 2. The AI-assistant has the features required for my tasks. 3. The AI-assistant has the ability to do what I want it to do.	 .90 .92 .83
Privacy and Security	(α = .90) (1=strongly disagree, 7= strongly agree) 1. I feel safe using the AI-assistant when performing tasks. 2. The AI-assistant implements measures to protect my data and privacy. 3. The AI-assistant ensures that my information is kept secure.	 .88 .94 .94
Perceived Usefulness	(α = .90) (1=strongly disagree, 7= strongly agree) 1. Using the AI-assistant improves my performance in tasks. 2. The AI-assistant increases my productivity in activities. 3. The AI-assistant enhances my effectiveness in completing tasks.	 .90 .87 .92
Perceived Enjoyment	(α = .91) (1=strongly disagree, 7= strongly agree) 1. I find using the AI-assistant to be enjoyable. 2. The actual process of using an AI-assistant is pleasant. 3. I have fun using the AI-assistant..	 .94 .92 .90

Constructs	Item	Factor loadings
Trusting Intention	(α = .86) (1=strongly disagree, 7= strongly agree) 1. I feel I can depend on the AI-assistant when completing tasks. 2. I can always rely on the AI-assistant for challenging tasks. 3. I feel I can count on the AI-assistant to support me with my activities.	.89 .88 .85
Continuance Intention	(α = .97) (1=strongly disagree, 7= strongly agree) 1. In the near future, I intend to continue using the AI-assistant. 2. I intend to keep using the AI-assistant. 3. I predict that I will continue using the AI-assistant.	.94 .96 .95

Appendix B: The questionnaire

Informed consent:

Trust in Large Language Models (LLMs): The Role of Human-Like and System-Like Trust Factors

Master's thesis – Pheebe Niewold, Erasmus University Rotterdam

You are invited to take part in a short (±8 minutes) anonymous survey about your perception of an AI assistant (e.g. ChatGPT, Microsoft Copilot, Claude). The goal is to better understand how trust in LLMs is formed in personal and work-related contexts.

Your participation is voluntary. You can stop at any time without giving a reason. All responses are required to ensure valid results. Your data will remain anonymous and will only be used for academic purposes (e.g., thesis and related publications). No personal data will be collected.

By clicking "Yes," you confirm:

- You have read this information
- You understand your rights (e.g., to withdraw)
- You agree to participate voluntarily

For questions, contact: 702665pn@student.eur.nl

Thank you for your time!

Eligibility

Before proceeding, please confirm:

- I confirm I am 18 years or older.

- Have you used a Large Language Model (LLM) in the past 12 months (e.g. ChatGPT, Microsoft Copilot, Claude, Deepseek)?

If you do not meet these criteria, you will be redirected to a thank-you page.

To ensure relevant responses, we ask you to indicate the primary context in which you use LLMs:

- Personal use (e.g., entertainment, personal projects, daily life tasks)
- Work-related use (e.g., professional tasks, workplace communication, coding)
- Both equally (personal and work-related use)

Context message:

Personal context:

Please answer the following questions based on your experiences using a LLM for personal tasks, including entertainment, personal projects, or daily life tasks.

Respond to each statement honestly based on your experiences in a personal context.

Work-related context:

Please answer the following questions based on your experiences using a LLM for work-related tasks, including professional projects, study, workplace communication, or coding.

Respond to each statement honestly based on your experiences in a work-related context.

Which Large Language Model (LLM) do you use most often?

- ChatGPT
- Microsoft Copilot
- Claude (Anthropic)
- DeepSeek
- Google Gemini
- Perplexity AI
- Other: ___

Questions

The following questions are about your perception of the effectiveness of "Selected Choice/ TextEntry of LLM" in performing tasks for personal use (e.g., entertainment, personal projects, daily life tasks)/ in performing tasks for work-related use (e.g., professional tasks, workplace communication, coding).

1. The AI-assistant is competent and effective in performing tasks.

2. The AI-assistant performs its role of assisting with tasks very well.
3. The AI-assistant is a capable and skilled assistant.

The following questions are about your familiarity with using “Selected Choice/ TextEntry of LLM”

1. I am familiar with the AI-assistant through using it before.
2. I am familiar with the AI-assistant through searching for information or help.
3. I am familiar with the AI-assistant through interacting with it to complete tasks.

The following questions are about “Selected Choice/ TextEntry of LLM”’s honesty and fairness in its actions.

1. The AI-assistant is truthful in its responses and actions when assisting with tasks.
2. The AI-assistant is honest.
3. The AI-assistant keeps its commitments when assisting with tasks.

The following questions are about how responsive “Selected Choice/ TextEntry of LLM’s is to your needs for personal use (e.g., entertainment, personal projects, daily life tasks)/ in performing tasks for work-related use (e.g., professional tasks, workplace communication, coding).

1. The AI-assistant provides helpful suggestions.
2. The AI-assistant offers guidance when needed to improve task completion.
3. The AI-assistant provides whatever help I need.

The following questions are about “Selected Choice/ TextEntry of LLM’s consistent performance over time.

1. The AI-assistant is a very reliable tool.
2. The AI-assistant does not fail me.
3. The AI-assistant consistently works as expected.

The following questions are about “Selected Choice/ TextEntry of LLM’s ability to execute tasks effectively.

1. The AI-assistant has the functionality I need.
2. The AI-assistant has the features required for my tasks.

3. The AI-assistant has the ability to do what I want it to do.

The following questions are about how “Selected Choice/ TextEntry of LLM” protects your data and privacy.

1. I feel safe using the AI-assistant when performing tasks.
2. The AI-assistant implements measures to protect my data and privacy.
3. The AI-assistant ensures that my information is kept secure.

The following questions are about how enjoyable it is to use “Selected Choice/ TextEntry of LLM” for personal tasks (e.g., entertainment, personal projects, daily life tasks)/ in performing tasks for work-related use (e.g., professional tasks, workplace communication, coding).

1. I find using the AI-assistant to be enjoyable.
2. The actual process of using an AI-assistant is pleasant.
3. I have fun using the AI-assistant.

The following questions are about how useful “Selected Choice/ TextEntry of LLM” is in improving your performance.

1. Using the AI-assistant improves my performance in tasks.
2. The AI-assistant increases my productivity in activities.
3. The AI-assistant enhances my effectiveness in completing tasks.

The following questions are about your willingness to trust “Selected Choice/ TextEntry of LLM”.

1. I feel I can depend on the AI-assistant when completing tasks.
2. I can always rely on the AI-assistant for challenging tasks.
3. I feel I can count on the AI-assistant to support me with my activities.

The following questions are about your intention to keep using “Selected Choice/ TextEntry of LLM.

1. In the near future, I intend to continue using the AI-assistant.
2. I intend to keep using the AI-assistant.
3. I predict that I will continue using the AI-assistant.

Appendix C: Invoice of Prolific

Invoice

Prolific

Prolific Academic Ltd
08991598
GB 233 6075 23
https://prolific.com
info@prolific.com
483 Green Lanes, London N13 4BS
United Kingdom

Billed to
Pheebe Niewold
Erasmus University
Burgemeester van Walsumweg 630
Rotterdam
Netherlands
3011MZ
NL

Invoice number
681e4176ed4f4658be417dec

Invoice date
09-05-2025

Item	Unit cost	Quantity	Tax rate
Platform fees	£8.33	1	20%
Study rewards	£25.00	1	NO VAT

Subtotal	£33.33
Tax 20%	£1.67
Total	£35.00
Status	**PAID**

Appendix D: AI Declaration and List of Prompts

Declaration Page: Use of Generative AI Tools in Thesis

Student Information

Name: Pheebe Niewold

Student ID: 702665pn

Course Name: Master Thesis CM5050

Supervisor Name: Dr. S. A. Rijsdijk

Date: 25th of June 2025

Declaration:

Acknowledgment of Generative AI Tools

I acknowledge that I am aware of the existence and functionality of generative artificial intelligence (AI) tools, which are capable of producing content such as text, images, and other creative works autonomously.

GenAI use would include, but not limited to:

- Generated content (e.g., ChatGPT, Quillbot) limited strictly to content that is not assessed (e.g., thesis title).
- ~~Writing improvements, including~~ grammar and spelling corrections (e.g., Grammarly)
- Language translation (e.g., DeepL), without generative AI alterations/improvements.
- Research task assistance (e.g., finding survey scales, qualitative coding verification, debugging code)
- Using GenAI as a search engine tool to find academic articles or books (e.g.,

☒ I declare that I have used generative AI tools, specifically ChatGPT, in the process of creating parts or components of my thesis. The purpose of using these tools was to aid in generating content or assisting with specific aspects of thesis work.

Extent of AI Usage

☒ I confirm that while I utilized generative AI tools to aid in content creation, the majority of the intellectual effort, creative input, and decision-making involved in completing the thesis were undertaken by me. I have enclosed the prompts/logging of the GenAI tool use in an appendix.

Ethical and Academic Integrity

☒ I understand the ethical implications and academic integrity concerns related to the use of AI tools in coursework. I assure that the AI-generated content was used responsibly, and any content derived from these tools has been appropriately cited and attributed according to the guidelines provided by the instructor and the course. I have taken necessary steps to distinguish between my original work and the AI-generated contributions. Any direct quotations, paraphrased content, or other forms of AI-generated material have been properly referenced in accordance with academic conventions.

☐ I declare that I have NOT used any generative AI tools and that the assignment concerned is my original work.

Signature: [digital signature]

Date of Signature: [Date of Submission]

By signing this declaration, I affirm that this declaration is accurate and truthful. I take full responsibility for the integrity of my assignment and am prepared to discuss and explain the role of generative AI tools in my creative process if required by the instructor or the Examination Board. I further affirm that I have used generative AI tools in accordance with ethical standards and academic integrity expectations.

Signature: PN

Date of Signature: 25th of June 2025

List of Prompts:

- "how to compute interaction terms in spss for an interaction between a dummy and continuous variable"
- "Can you help me rewrite this sentence so it sounds more academic?"
- "How do I make the transition between these two sections smoother?"
- "How can I split this paragraph into two?"
- "Can you suggest a subtitle for this paragraph in my theoretical framework?"
- "Do you have suggestions for a title for my thesis?"